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13. ABSTRACT *(Maximum 200 Words)*

In computer-aided diagnosis, temporal change overtime can be a key piece of information in treatment monitoring and disease tracking applications. In these applications, change detection depends on the ability to align the images of the sequence to a common axis, and the ability to build up memory about the image scene overtime. The process of aligning images to a common axis is termed image registration. The image scene representation is called site model. In this research we developed a novel registration technique to align temporal sequences of the same patient that will facilitate the construction of scene memory or site model with the ultimate goal of performing change detection. We have developed a statistical model supported approach for enhanced segmentation and extraction of suspicious mass areas from mammographic images. With an appropriate statistical description of various discriminate characteristics of both true and false candidates from the localized areas, an improved mass detection may be achieved in computer-aided diagnosis. In this study, one type of morphological operation is derived to enhance disease patterns of suspected masses by cleaning up unrelated background clutters, and a model-based image segmentation is performed to localize the suspected mass areas using stochastic relaxation labeling scheme.

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5. INTRODUCTION

Based on preliminary evidence from combined change detection and neural network classifier in our CAD research, the **purpose** of the project is to develop an automatic change detection method to quantitatively extract the clinically important changes of suspicious lesions, upgrade the existing CAD system, and thus improve the clinical diagnosis of breast cancer. We will build a site model for each individual patient for monitoring the breast tissue changes and extend our current research on image registration, soft tissue modeling, and image segmentation, to the early detection of breast cancer. **Specific aims** include: 1) registration and segmentation of deformable breast tissue structures across a series of mammograms; 2) construction of a site model of the mammogram for individual patients showing the locations of regions of interest and associated diagnostic information; 3) identification of clinically significant changes in both global and local mass areas within the breast; and 4) integration and evaluation of the developed techniques with existing CAD prototype. At conclusion of this project, we anticipate achieving the following: 1) establish a reliable technique of monitoring breast tissue changes associated with cancerous masses; 2) deliver a CAD prototype that can incorporate tissue change information from additional mammograms; 3) evaluate the merit of combining change detection and CAD for improved clinical diagnosis using multiple mammograms; and 4) acquire the experience necessary to explore multimodality imaging for unified detection, diagnosis and treatment assessment of breast cancer.

6. BODY-Annual Summary

The **long-term** goal of this career development project is to develop image guided diagnosis methodology through change detection in multimodality image sequences for breast cancer. The research requires the knowledge of image analysis, image registration, computer graphics, and information theory.

As the training accomplishments during the first year, I have developed a close consultation relationship with Dr. Matthew Freedman (radiologist) and Dr. Ben Lo (medical physicist) at Georgetown University Medical Center. I have also developed a strategic collaboration with Dr. Robert Clarke (Department of Oncology) at the Lombardi Cancer Center. Through them, I have learned more about breast cancer at both imaging and molecular levels. I am now an invited member attending the weekly meeting organized by Dr. Freedman and Dr. Clarke.

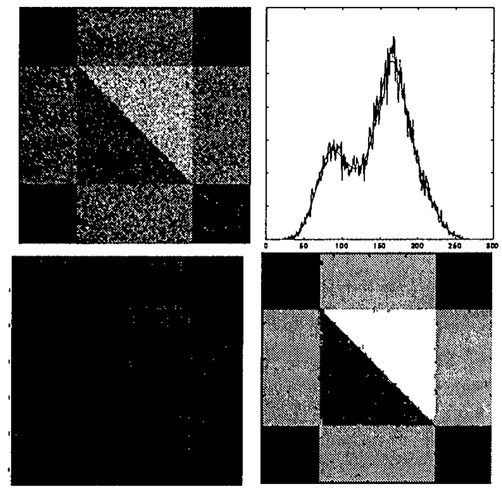

Figure 1. Image segmentation with digital phantom.

Based on this, I have also developed my own research group, as the lab director, with one research associate professor and eight graduate students. I am currently serving as the major advisor for three graduate students who are specifically working on the breast cancer research. I also served as a penal member of the Peer-Review Committee for Department of Defense Breast Cancer Research Program in 1999. I have been serving as a member of the Technical Committee (TC) on Neural Networks for Signal Processing (NNSP) in IEEE since 1999.

As the research accomplishments during the first year, I have first identified the following tasks as the first step of the project:

1. Analyze medical image (both mammograms and magnetic resonance image) that contains multiple anatomical objects through direct 2-D and/or 3-D tissue quantification and region segmentation. In particular, the tissue quantification is performed based on the standard finite normal mixture (SFNM) modeling of pixel image distribution, AIC and MDL guided model selection, and EM maximum likelihood model estimation. The region segmentation (e.g., the mass sites from the mammograms) is achieved based on inhomogeneous MRF modeling of context images and relaxation labeling of pixel memberships.
2. Construct a patient specific model (i.e., the site model) based on the outcome of image analysis including objects, surface, and boundaries, of the normal tissues and detected/suspected lesions. This will provide a framework for (1) high accuracy change monitoring considering the patient variation and (2) effective data fusion incorporating prior/domain specific information.
3. Develop a multiple step algorithm for 2-D and 3-D image registration of image sequence data sets and multimodality image data sets. It consists of three major components: (1) principle axes registration (PAR), (2) site

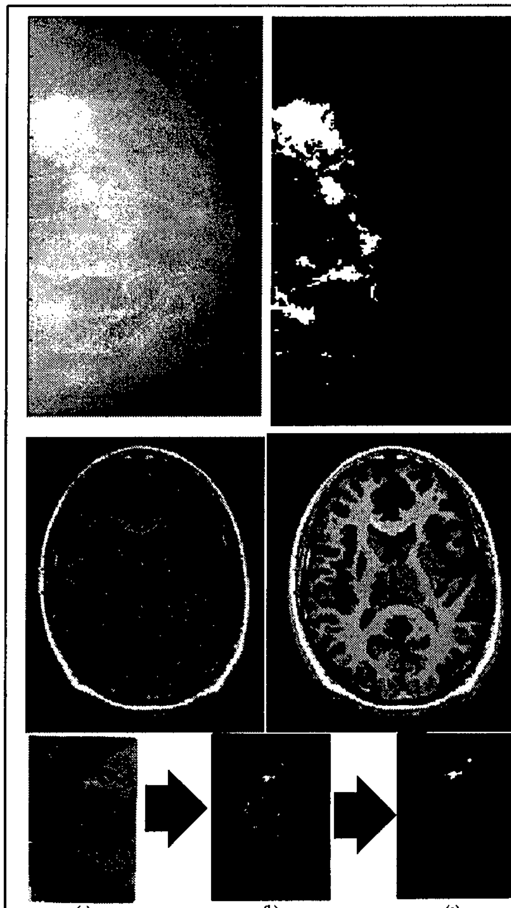

Figure 2. Mammogram segmentation (Up: global). Multiple level MR image segmentation (Middle). Lesion site segmentation (Down: local).

model support control feature alignment with localized PAR, and (3) raw data matching via maximizing the mutual information (MI) between the two images.

4. Apply new algorithms to perform change detection from a set of sequence images, where the clinical objectives are lesion verification/detection, lesion localization, and change quantification.

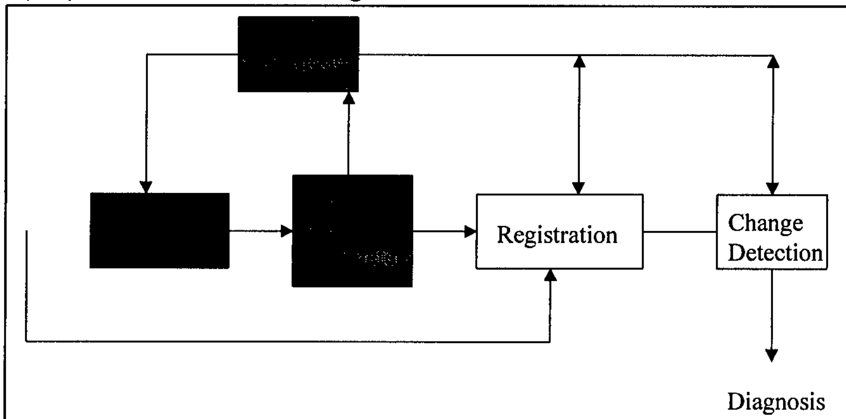

Figure 3. Flowchart of patient specific site model construction.

Follow this plan, major research accomplishments include:

6.1 Lesion site segmentation

We have developed a new algorithm to perform lesion site segmentation as well as whole image segmentation. We have implemented the computer codes and pilot tested its effective applications to the digital phantoms, mammograms, MR images, and ultrasound images. The algorithm includes dual morphological filtering for signal enhancement and statistical model based tissue quantification and lesion segmentation [1,2]. Figure 1 shows the results of segmentation algorithm with simulated digital phantom. Figure 2 shows the results of the applications to multimodality images. Our results have indicated that all the suspected lesion sites were successfully detected and the areas were accurately segmented. Detailed discussions please see the attached manuscripts.

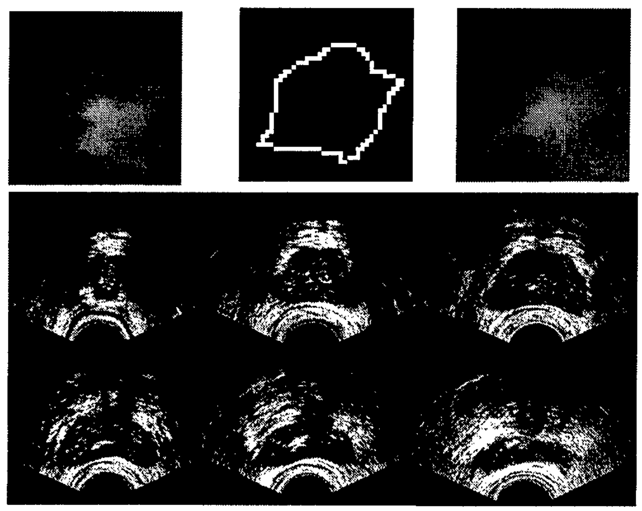
Figure 4. Site model overlay with the raw images.

6.2 Construction of patient specific site model for change detection

Based image analysis results and all available clinical diagnostic information, we pilot constructed a patient specific site model. This model is a mathematical formulation of multimedia scene information, mainly including object geometry (e.g., object location), reference labels (e.g., control points and/or objects), and expert's knowledge (e.g., lesion index, diagnostic comments, etc.). Figure 3 shows the schematic flowchart of the approach. Figure 4 illustrates the partial results of the site models.

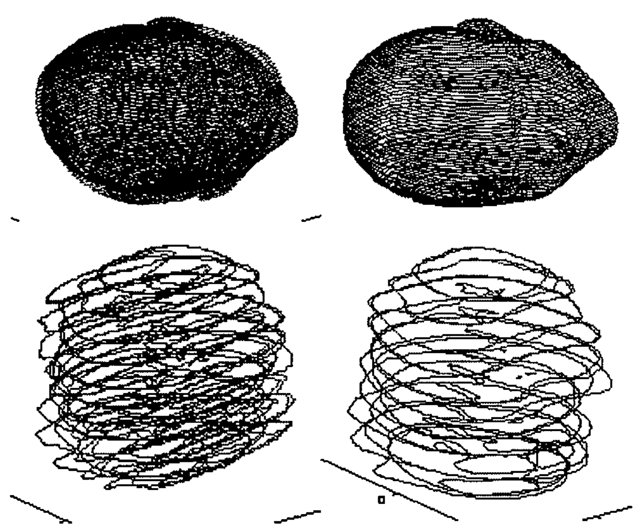
Figure 5. Multi-object based global principal-axes 3D registration.

6.3 Development of multiple-step image registration algorithm

To achieve accurate change detection for the diagnosis of early breast cancer, image registration of the image sequence of the same patient is a crucial step. This step is being achieved through multi-object principal-axes alignment, site model supported skeleton mapping, and surface based

deformable warping. We have we theoretically verified the optimality of the method in the cases of lacking in point-pair correspondence, by considering both image registration can be divided into two categories: (1) object-imager positioning and (2) object-object mapping.

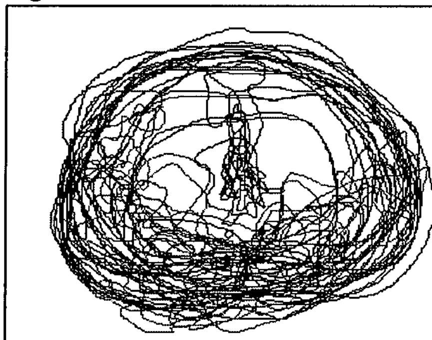

Figure 6. Multiple lesion mapping.

Let an image be denoted by a function F(x,y,z) where F is the gray-level of the pixel. The corresponding graphics is denoted by a set {(x,y,z)} where (x,y,z) is the point based on which the graphics is formed. Graphics that may be considered as a representation of the image through a pathway of segmentation, boundary formation, surface representation, or feature extraction. A site model may be constructed by integrating F(x,y,z) and {(x,y,z)} to describe a particular site. Thus, image registration should include the following components: assumptions, criterion, principle, and transformation. Our research has indicated that the major problems in most existing image registration algorithms are: 1) difficult in unifying these four components; 2) difficult in proving the optimality of a particular method; and 3) difficult in resolving the conflict between registration and "change".

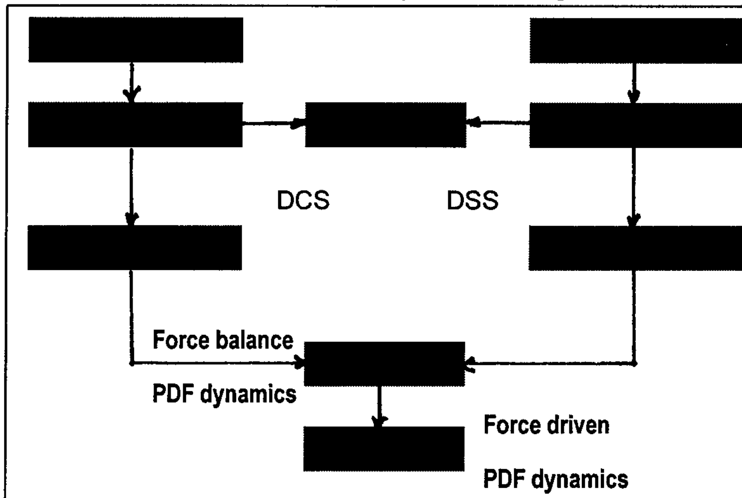

Figure 7. Schematic frame of non-rigid deformable registration.

We have implemented a global principal-axes registration (GPAR) algorithm. Its operation is based on a set of "control points/objects" extracted/identified from the images. Since the set of control points/objects is selected, it can be highly insensitive to the "change". When point correspondence is available and least square error is used as the criterion function, it has been shown that the solution can be obtained through a point set matching, where the similarity transformation is derived directly from a cross-covariance matrix. This approach may not be applicable to control object matching if the point correspondence is unavailable. However, if a point-based skeleton matching is pursued, this method may be applicable. In addition, it has not been shown that this approach works for "scaling" operation though it is highly possible. When point correspondence is unavailable and least relative entropy is used as the criterion function, it can be shown that the solution is obtained through a probability density function matching, where the similarity transformation is derived from the two auto-covariance matrices. Unfortunately, there are two problems associate with the present approach. First, the "rotation" operation is defined by the similarity transformation matrix, in which the eigen-vectors corresponds to the principal axes of the sets. However, although the "orientation" of each of the principal axes is uniquely determined, it can have two opposite "directions" reflected by the sign of the corresponding eigen-value. This event is called "reflection" (i.e., rotation with p+q instead of q) and can be corrected by the method proposed by T. S. Huang. Second, pseudo-symmetry of the control point/object set will cause a large intrinsic error in the "rotation" operation, where the order of the eigen-values may be incorrectly determined. This problem may be avoided by a careful selection of the control point/objects.

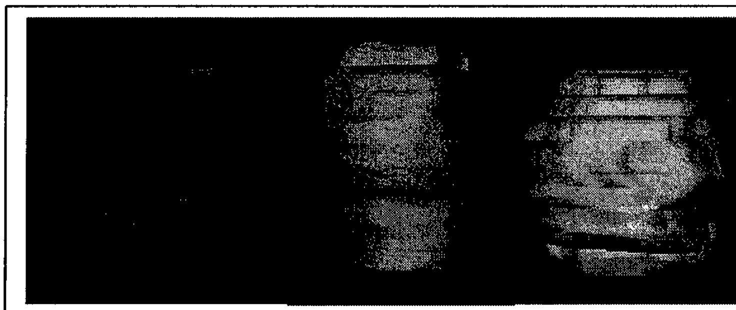

Figure 8. Preliminary result of deformable registration.

We have put considerable effort to guide the control object selection. Our experience indicate that the control points/objects should be selected according to the following criteria: 1) A group of control objects with each of the objects having the same order of the points (via interpolation or down-sampling; 2) The global geometric configuration of the control objects, i.e., the spatial distribution, should form a unique and non-symmetry pattern; 3) Each of the control objects prefers its unique and non-symmetry shape; 4) The local geometric shape of the control objects allows small distortions; and 5) The global geometric configuration of the control objects assumes shift-invariant. In addition, a patient site model should contain a set of control points/objects, though the site model may contain much more information using different media.

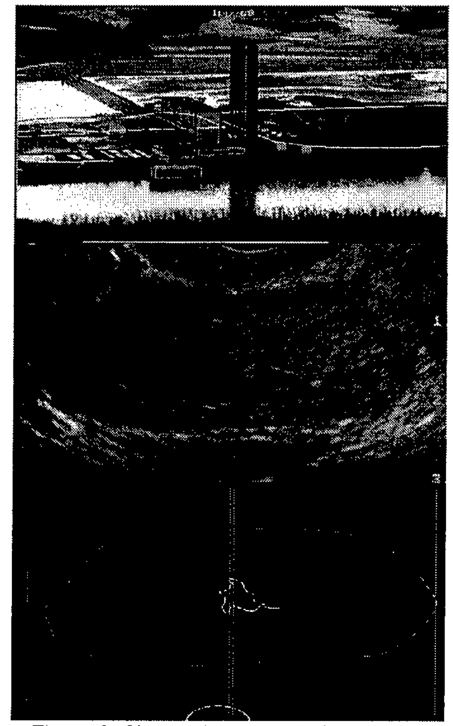

Figure 9. Site model supported model-to-image registration for change detection.

6.4 Integration of change detection with CAD

We have pilot integrated our preliminary change detection capability with the existing CAD system. The purpose of change detection is twofold: (1) to detection suspected lesion sites as the candidate "input" to the CAD system, and (2) to monitor the changes of the "output" lesion sites selected by the CAD system for follow-up diagnosis. This is the major objective in the following year research. However, fruitful preliminary results can be found in our attached manuscripts [1,2,3].

In summary, we have developed a statistical model supported approach for enhanced segmentation and extraction of suspicious mass areas from mammographic images. With an appropriate statistical description of various discriminate characteristics of both true and false candidates from the localized areas, an improved mass detection may be achieved in computer-aided diagnosis. In this study, one type of morphological operation is derived to enhance disease patterns of suspected masses by cleaning up unrelated background clutters, and a model-based image segmentation is performed to localize the suspected mass areas using stochastic relaxation labeling scheme. We discuss the importance of model selection when a finite generalized Gaussian mixture is employed, and use the information theoretic criteria to determine the optimal model structure and parameters. Examples are presented to show the effectiveness of the proposed methods on mass lesion enhancement and segmentation when applied to mammographical images. Experimental results demonstrate that the proposed method achieves a very satisfactory performance as a pre-processing procedure for mass detection in computer-aided diagnosis.

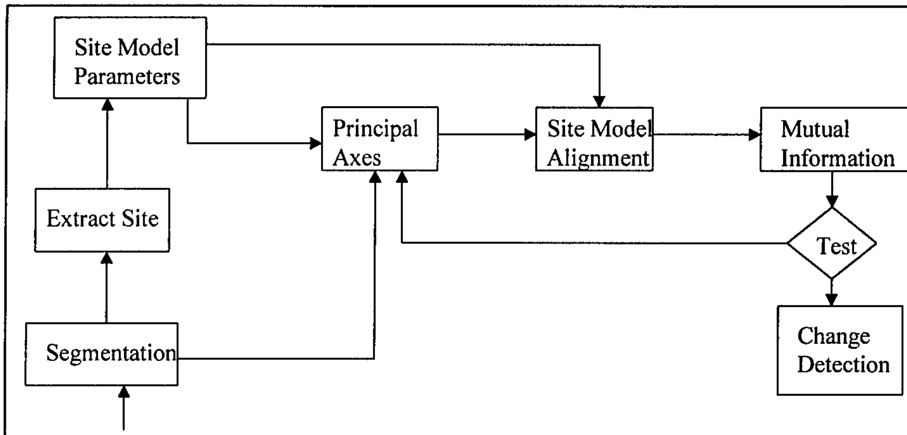

Figure 10. Schematic flowchart of the hybrid image registration algorithm.

Based on the enhanced segmentation of suspicious mass areas, further development of computer aided mass detection may be decomposed into three distinctive machine learning tasks: (1) construction of the featured knowledge database; (2) mapping of the classified and/or unclassified data points in the database; and (3) development of an intelligent user interface. A decision support system may then be constructed as a complementary machine observer that should enhance the radiologists performance in

mass detection. We adopt a mathematical feature extraction procedure to construct the featured knowledge database from all the suspicious mass sites localized by the enhanced segmentation. The optimal mapping of the data points is then obtained by learning the generalized normal mixtures and decision boundaries, where a probabilistic modular neural network is developed to carry out both soft and hard clustering. A visual explanation of the decision making is further invented as a clinical support, based on an interactive visualization hierarchy through the probabilistic principal component projections of the knowledge database and the localized optimal displays of the retrieved raw data. A prototype system is developed and pilot tested to demonstrate the applicability of this framework to mammographic mass detection.

7: APPENDICES

7.1 Key Research Accomplishments

- We are creating a unique mammography database consisting of a sequence of mammograms of the same patient taken over a period of time. This provides an opportunity of tracking various changes of the suspected mass lesions. In addition, we have started to acquire the corresponding three-dimensional (3-D) magnetic resonance (MR) images of the same patient with the purpose of validating the computer analysis results from the mammograms using the 3-D MR images.
- A morphological mass signal enhancement method is developed that has shown its effectiveness on achieving an improved lesion localization and site area segmentation. In addition, a statistical model-based segmentation algorithm is implemented to accurately extract mass-like site areas. One manuscript on this topic has been submitted to *IEEE Transactions on Medical Imaging.*
- We have examined a total of nine features associated with mass-like lesion description. We have developed a visual database mapping technique to interpret the machine learning and decision making. Our preliminary experiment has shown that three of the nine features form a good differentiation vector. One manuscript on this topic has been submitted to *IEEE Transactions on Medical Imaging.*
- We have proposed a hybrid algorithm for 2-D and/or 3-D rigid image registration that is crucial to the accurate change detection. We have implemented multi-object principal-axes registration algorithm and are currently working on the mutual information based registration fine-tuning procedure.
- We have proposed a hybrid algorithm for 2-D and/or 3-D non-rigid image registration, using local principal-axes skeleton mapping and surface based deformable warping with bilinear interpolation technique.

7.2 Reportable Outcomes

1) H. Li, **Y. Wang**, K-J R. Liu, S-H B. Lo, and M. T. Freedman, "Statistical Model Supported Approach to Radiographic Mass Detection I: Improving Lesion Characterization by Morphological Filtering and Site Segmentation," Submitted to *IEEE Transactions on Medical Imaging* 1999.
2) H. Li, **Y. Wang**, K-J R. Liu, S-H B. Lo, and M. T. Freedman, "Statistical Model Supported Approach to Radiographic Mass Detection II: Decision Making through Minimax Entropy Modeling and Modular Neural Networks," Submitted to *IEEE Transactions on Medical Imaging* 1999.
3) J. Xuan, T. Adali, **Y. Wang**, and E. Siegel, "Automatic Detection of Foreign Objects in Computed Radiography," submitted to *SPIE Journal of Biomedical Optics*, 1999.
4) **Y. Wang**, "A spectator's restricted view on computer-aided diagnosis," An invited presentation at the Siemens Corporate Research, Inc., Princeton, December 1998.
5) A multimodality breast image database: 2-D mammographic and 3-D magnetic resonance image sequences with 20 patient cases.
6) M. T. Freedman and **Y. Wang**, "Change Detection and Soft Tissue Modeling in Breast Cancer Imaging," a grant award from the Siemens Corporate Research, Inc., $15,000, 4/1/99-6/30/99.

Automatic Detection of Foreign Objects in Computed Radiography

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ABSTRACT

This paper presents an effective two-step scheme for automatic object detection in computed radiography (CR) images. First, various structure elements of the morphological filters, designed by incorporating available mophological features of the objects of interets including their sizes and rough shape descriptions, are used to effectively distinguish the foreign object candidates from the complex background structures. Secondly, since the boundaries of the objects are the key features in reflecting object characteristics, active contour models are employed to accurately outline the mophological shapes of the suspicious foreign objects to furhter reduce the rate of false alarms. The actual detection scheme is accomplished by jointly using these two steps. The proposed methods are tested with a database of 50 hand-wrist computed radiographic images containing various types of foreign objects. Our experimental results demonstrate that the combined use of morphological filters and active contour models can provide an effective automatic detection of foreign objects in CR images achieving good sensitivity and specificity, and the accurate descriptions of the object mophological characteristics.

Keywords: Object detection, morphological filters, active contour models, computed radiography.

This work was partially supported by the US Army Medical Research and Materiel Command under grant DAMD17-98-1-8045.

I Introduction

Object detection and characterization through medical imaging technologies are among the major clinically-driven tasks towards the ultimate goal of diagnosis and treatment of diseases. In particular, newly introduced computed radiography (CR) has shown the potential to replace screen-film radiography (SFR) in routine clinical practice due to its numerous advantages including greater dynamic range and wider exposure latitude [10]. Some quantitative comparison of CR and SFR in detection of specific diseases such as pneumothorax has demonstrated their equal detectibility at equivalent exposure factors of two imaging systems [5, 9]. More importantly, due to its native digital storage form, image processing and analysis techniques can be seamlessly integrated into the CR system. The objective of this work is to develope an automatic foreign object detection algorithm which locates foreign objects in CR images and provides their accurate boundary descriptions for further diagnosis and treatment.

Object detection in CR images can be accomplished through an accurate representation of the object of interest in terms of its location, size, and shape description. In general, there are two general approaches: (1) data-directed (bottom-up) approach such as edge detection [3] and region growing [7]; and (2) goal-directed (top-down) approach as in knowledge-guided boundary detection [11]. The bottom-up approach operates on the image only based on individual gray level values to extract the object boundary or to obtain the object region, while the top-down approach relies entirely on *a priori* constraints regarding the location and shape of the object of interest. In this paper, we propose an automatic object detection technique which incorporates fundamental object characteristics such as the size and generic shape information to initially localize the object of interest from the scene image, and then to confirm the correct presence of suspicious targets through a boundary refining procedure.

The presentation is organized as follows. In section II, we present brief review on object detection problem and address the difficulties of object detection in CR images. The proposed new approache is described in detail in Section III where two major steps (i.e., morphological filtersa and active contour models) are explained. In section IV, the application of approach to a set of hand-wrist CR images is reported with the experimental results presented. Discussion and conclusion are provided in section V.

II Problem Statement

Automatic object detection is still a difficult task in medical image processing since many clinically acquired medical images may be noisy and low contrast. In addition, the presence of the objects in question is frequently self-occluded or partially transparent with uncertain position, size, orientation, shape, motion, etc. An example is shown in Figure 1. Therefore, the precise boundary characterization of these objects may be very difficult.

Most research on object detection falls into two categories: (1) edge detection and (2) region growing. Many edge detection algorithms have been proposed based on the assumption that different objects have different intensity values [3]. However, since most medical images are low contrast and noisy, simple application of edge detection will most likely give broken boundaries of objects. On the other hand, region-based techniques often fail to yield the desired structure due to the difficulty of choosing a reasonable starting "seed" point, an appropriate growing rule or a suitable stopping rule. More recently, knowledge-guided boundary finding methods are proposed to extract geometric shapes based on site models which are best suited for objects poorly described by features or parts. Boundary descriptions using local information fails to give satisfactory results in practice because of poor-contrast boundary regions due to occluding and occluded objects, adverse viewing conditions and noise. And further difficulty arises when we try to find a model to describe a relatively broad class of shapes such as that of deformable objects. Such difficulty in knowledge representation largely hinders the knowledge-guided boundary finding approach for object detection problem.

To tackle the problems of forementioned approaches, two important research areas attracted our attention: active contour models and morphological filters. In this paper, we propose to combine morphological filters with active contour models to automatically detect objects of interest in CR images. The diagram of our automatic foreign object detection algorithm is illustrated in Figure 1. Morphological filters are first applied to locate the objects by concentrating on location and size information but with a rough shape information. Then active contour models are used to modify the contours of the detected objects. In specific, we model the initial contour extracted by morphological filters as a physical object, and the data as an external force to which the object is attracted, and an iterative procedure can then be initiated

to cause the active contour to move toward the data and ultimately conform to it.

The motivation of jointly using active contour models and mathematical mopgological filters can be briefly explained as follows. Active contour models, also called snakes, have recently been developed for finding optimal contours which offer the advantage that the final form of a contour can be influenced by feedback from a higher-level process or an interactive user [8]. The initial contour is generally placed near the boundary of an object under consideration, then image forces draw the contour to the object boundary. Therefore, active contour models are usually used to *interactively* or *semi-automatically* extract object boundaries. On the other hand, mathematical morphology has been an important method for the analysis of geometric structures of objects [2, 6]. It aims at analyzing the shape and form of objects by using mathematical set theory, topology, lattice algebra, and random functions. As nonlinear and shape-focused filters, morphological filters can suppress the background but still retain size and location information with a fair amount of accuracy. The geometric nature of the morphological filters is well suited to perform object detection task.

III Methods

In order to achieve an automatic foriegn onject detection in CR images, the proposed approache consists of two major steps: the first step is to detect the foreign objects by using morphological filters – gray-scale *background reduction* and binary *opening* operation; Then the active contour models are followed to refine the boundaries of those detected foreign objects. In this section, we present detailed methametical formulation of these two methods and describe our two-step algorithm in implementing their functions.

III.1 Foreign Object Detection

Morphological filters are used to detect the foreign objects in CR images whose background is defined by complex bone structures, since morphological filters allow us to suppress the background while retaining size and location information [2], [6]. Features brighter than the background, but smaller than the structuring element, can be removed from an image with the opening operation. Thus, if the features of interest are brighter than the background, opening

the image by a structuring element bigger than the largest feature will remove the features from the image leaving behind an estimate of the background. Subtracting the estimate of the background from the original image extracts the features of interest. The morphological filter, *background reduction*, is performed as follows [2]:

$$\text{Background reduction} = \mathbf{A} - (\mathbf{A} \circ \mathbf{B}), \tag{1}$$

where $\mathbf{A}$ is the original image, $\mathbf{B}$ is the structuring element whose size is larger than any of the brighter features of interest, and "$\circ$" is the gray-scale *opening* operation, which is defined as:

$$\mathbf{A} \circ \mathbf{B} = (\mathbf{A} \ominus \mathbf{B}) \oplus \mathbf{B}. \tag{2}$$

In the above equation, $\oplus$ and $\ominus$ are gray-scale *dilation* and *erosion* operations respectively. If we denote the gray-scale dilation image of an image $\mathbf{A}$ by a structuring element $\mathbf{B}$ as $\mathbf{C} = \mathbf{A} \oplus \mathbf{B}$, we can define the element of $\mathbf{C}$, $c(x, y)$, as

$$c(x,y) = \max\{a(x-i, y-j) + b(i,j) | (x-i, y-j) \in D_a; (i,j) \in D_b\}. \tag{3}$$

where $a(x,y)$ is the element of $\mathbf{A}$ and $b(x,y)$ the element of $\mathbf{B}$; D_a and D_b are the domains of $\mathbf{A}$ and $\mathbf{B}$, respectively.

Similarly, an image $\mathbf{C}$, obtained by gray-scale eroding $\mathbf{A}$ by $\mathbf{B}$, denoted by $\mathbf{C} = \mathbf{A} \ominus \mathbf{B}$, can be defined by

$$c(x,y) = \min\{a(x-i, y-j) - b(i,j) | (x-i, y-j) \in D_a; (i,j) \in D_b\}, \tag{4}$$

Note that the location of the extracted features by *background reduction* will be exactly the same as those in the original image. In gray-scale morphology, the structuring element can be any three-dimensional structure such as cylinder or hemisphere. In this application, we use $n \times n$ hemispherical mask whose individual element is given by

$$w(x,y) = \sqrt{g^2 - (gx/k)^2 - (gy/k)^2}, \tag{5}$$

where $w(x, y)$ is the intensity at location (x, y) of the hemispherical structuring element, g is the peak intensity at the center of the mask, x and y lie in the range $[-k, k]$ with $k = (n-1)/2$.

Some small bright bony structures are inevitablely detected as foreign objects in hand-wrist CR images, but they can be easily delineated by using the size information as their size is usually much smaller than that of the foreign objects of interest. Therefore we convert the gray-level resulting image from the *background reduction* to a binary image by thresholding. A binary opening operation is then applied to specifically extract only the foreign objects. The binary *opening* of set $\mathbf{A}$ by structuring element $\mathbf{B}$, denoted by $\mathbf{A} \circ \mathbf{B}$, can be defined as [6]

$$\mathbf{A} \circ \mathbf{B} = (\mathbf{A} \ominus \mathbf{B}) \oplus \mathbf{B}, \tag{6}$$

where, $\oplus$ and $\ominus$ denote binary *dilation* and *erosion*, respectively. In other words, equation (6) says that the opening of $\mathbf{A}$ by $\mathbf{B}$ is simply the erosion of $\mathbf{A}$ by $\mathbf{B}$, followed by a dilation of the result by $\mathbf{B}$. For completeness, we give the definitions of binary *dilation* and *erosion* as follows. Let $\mathbf{A}$ and $\mathbf{B}$ be sets in Z^2, the binary *dilation* of $\mathbf{A}$ by $\mathbf{B}$, denoted by $\mathbf{A} \oplus \mathbf{B}$, is defined as

$$\mathbf{A} \oplus \mathbf{B} = \{(x, y) | (\hat{\mathbf{B}})_{(x,y)} \cap \mathbf{A} \neq \emptyset\}, \tag{7}$$

where $\hat{\mathbf{B}} = \{(x, y) | x = -i, y = -j, \text{ for } (i, j) \in \mathbf{B}\}$ and $(\mathbf{A})_{(x,y)} = \{(c, d) | c = i + x, d = j + y,$ for $(i, j) \in \mathbf{A}\}$. The binary *erosion* of $\mathbf{A}$ and $\mathbf{B}$, denoted by $\mathbf{A} \ominus \mathbf{B}$, is defined as

$$\mathbf{A} \ominus \mathbf{B} = \{(x, y) | (\hat{\mathbf{B}})_{(x,y)} \subseteq \mathbf{A}\}. \tag{8}$$

which, in words, says that the erosion of $\mathbf{A}$ by $\mathbf{B}$ is the set of all points (x, y) such that $\mathbf{B}$, translated by (x, y), is contained in $\mathbf{A}$.

III.2 Foreign Object Contour Modification

The active contour models, snakes, are used to modify the contours of the foreign objects detected by morphological filters as explained in the previous section. Starting from the initial boundary of the detected foreign object, active contour model uses data, gradient image, as an external force to cause the initial contour to move toward the data and ultimately conform to it. The active contour model, snake, is defined as the following mapping [4]:

$$\begin{aligned} \Omega = [0,1] &\rightarrow \Re^2 \\ s &\mapsto v(s) = (x(s), y(s)). \end{aligned} \tag{9}$$

We define an active contour model (snake) as a space of admissible deformations Ad and a functional E to minimize. This functional represents the energy of the model and has the form

$$\begin{aligned} E : Ad &\rightarrow \Re \\ v &\mapsto E(v) = \int_{\Omega} w_1 |v'(s)|^2 + w_2 |v''(s)|^2 + P(v(s)) ds, \end{aligned} \tag{10}$$

where the primes denote differentiation and P the potential associated with the external forces. The mechanical properties of the model are controlled by the functions w_j. Their choice determines the elasticity and rigidity of the model. If v is a local minimum for E, it satisfies the associated Euler-Langrange equation [4]:

$$-(w_1 v')' + (w_2 v'')'' + \bigtriangledown P(v) = 0. \tag{11}$$

To obtain the final solution of v, a variational calculus method is originally proposed by Kass [8], while the dynamic programming method developed by Amini *et al.* allows addition of hard constraints to obtain a more desirable behavior of the snakes [1]. Recently a fast algorithm has been developed by using a greedy algorithm and can be found in [12]. In this paper, we use this greedy algorithm to modify the boundaries of foreign objects where the external forces are the gradient image data.

IV Experimental Results and Discussions

In order to validate the effectiveness of the proposed method in automatic foriegn object detection in CR images, intensive computer experiments with both simulated and real cases have been conducted. In this study, we have acquired three different sets of CR images taken from both phantom and cadaver hand specimens. In all these cases, the images are embedded

with some small foreign objects with different sizes, shapes, and materials (like plastic, glass, graphite, and wood). The CR images are digitally acquired with a size of 1700×2000 and a gray-level resolution of 10bits/pixel. An example is shown in Figure 2. Since in real-world clinical practice, CR images may be taken with varying radiation dosage depending upon the parameter settings, and it is desirable to obrain CR images with low radiation dosage while maintaining good detectibility, our testing database has been designed to cover a broad of cases with by various radiation dosage [9].

The gray-scale morphological filter, *background reduction*, is applied to the original image to detect the foreign objects with different location, size, shape, and materials. The structuring element is chosen as $n \times n$ hemispherical mask where n (43 in this experiment) corresponds to the largest size among those foreign objects of interest. The initial detected foreign objects are shown in Figure 3 after application of the gray-scale morphological filter for *background reduction.* As we can see from Figure 3 all the foreign objects of interest are detected without any missing. This result demonstrates that morphological filter can effectively capture the location and size information of the objects of interest. However, some redundant tiny spots are produced by very bright bony structures. To delineate those small redundant spots, we convert the gray-level outcome from the above step into binary image simply by thresholding, (see Figure 4). Then, we apply a binary *opening* operator to explicitly extract only the foreign objects as demonstrated in Figure 5.

The next step is to refine the boundaries of those detected foreign objects by active contour models. Taking the result from morphological filters as initial contour (Figure 6) and the gradient image as the external forces, we use the fast greedy algorithm to gradually move the initial contour to the final boundary by finding the minimum energy of the active contour model. The final boundaries of detected foreign objects are shown in Figure 7. As we can see, the detected boundaries conform very well to those of the foreign objects regardless of their different locations, sizes, shapes, and materials.

However, our experience also suggests that foreign object detection could be a very difficult problem. For example, when the acquired set of hand-wrist CR images embedded with some tiny invading objects, it is very difficult to define the true boundaries of the objects by performing either edge detection or region growing, and direct application of mophological fil-

tering maight be problematic. In other cases, when the CR images are taken with low dosage, the contrast will be degradated which furhter complicates the detection task especially for the complex bone structures that exist as the background in CR images. In this study, morphological filters are used to tackle the object detection problem by focusing on location and size of the objects but providing only rough shape information. Then, active contour models, which are capable of capturing accurate shape information, are used to refine the initially obtained rough boundaries.

V Conclusion

In this paper we have presented an automatic foreign object detection algorithm by using morphological filters and active contour models. The morphological filters are used to detect the objects of interest, focusing on the location and size information but a rough shape information, to provide the initial contours to active contour models. The active contour models are subsequently employed to refine the boundaries of the detected foreign objects since they can successfully capture the shape information. The algorithm has been applied to hand-wrist CR images to detect foreign objects with different locations, sizes, shapes, and materials. The experimental results demonstrate that the new automatic foreign object detection algorithm provides the location of the objects of interest with their accurate boundary descriptions.

The automatic foreign object detection algorithm has been further integrated into our task-oriented image quality evaluation method which fully takes account the clinical purposes of the medical images [14]. The task-oriented image quality evaluation method has proven to be very effective in assessment of CR image quality for radiation dose optimization [15]. In this particular CR study, we can quantify the quality of those images acquired with different radiation doses by comparing their detected boundaries of the foreign objects and their segmented bone structures in addition to the wavelet analysis. The experimental results are consistent with the radiologists' subjective evaluation as reported in [9]. In conclusion, the foreign object detection algorithm developed in this paper plays a significant role in the task-oriented CR image quality evaluation technique to optimize radiation dosage and hence reduce the amount of unnecessary radiation administered to patients during diagnostic procedure.

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